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HYBRID FUNDS: THE RIGHT MIX OF ACTIVE AND PASSIVE INVESTMENT STRATEGIES?

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Abstract:

Hybrid funds have almost quadrupled since 2003. This is puzzling given that prior research has found no evidence of hybrid funds outperforming passive products. Using data on the American market there is evidence of positive alphas and hybrid funds outperforming active funds after fees, mainly given to market timing ability. Hybrid funds trade more when they find short-term opportunities of profit but those that have higher turnover are not the best performing. Finally, there is no conclusive evidence that investors invest more on hybrid funds just because of their classification, without taking other characteristics into account.

Keywords: Hybrid Funds, Mutual Funds, Asset Management, Active Share

1. Introduction

Since 2010 that passive mutual funds have had larger capital inflows than active funds on a yearly basis. In fact, over the past four years, while active funds lost capital, passive investments received record capital inflows. Over the course of 2016, active funds had net outflows of \$340.1 billion against \$504.8 billion net inflows to passive funds (Morningstar Direct Asset Flows Commentary, 2017).

While some investment managers trade actively to achieve alpha, many believe these funds do not provide positive risk-adjusted returns after-fees. The simple doubt on the performance of active funds, allied with relatively high management fees has led investors to tilt their portfolios into cheaper passive and semi-passive investments. Among these, exchange traded funds (ETF's) and index funds are the most commonly used. While ETF's have been broadly studied, two specific types of index funds have not: enhanced index funds (EIF) and index based funds (IBF). These can be called hybrid funds since they provide a mix between active and passive investment. Table 1 shows the evolution of these hybrid funds and their traditional counterparts on the United States (US) market.

Table 1 - Evolution of the Industry in the United States

	Panel A: Evolution of Number of Funds			Panel B: Evolution of Total Net Assets (in M \$)		
	Active	Hybrid	Passive	Active	Hybrid	Passive
2003	36 016	574	1 620	34 334 849	319 543	3 013 410
2004	37 713	1 196	2 993	40 838 173	817 601	6 517 106
2005	40 255	1 238	3 380	47 297 971	1 034 195	7 959 956
2006	43 500	1 238	3 940	56 116 332	1 341 312	9 825 006
2007	44 392	1 315	4 849	65 910 107	1 706 535	12 399 033
2008	43 864	1 537	5 342	56 909 945	1 702 388	11 792 118
2009	42 184	1 781	5 477	47 049 685	1 733 755	10 757 537
2010	41 911	1 926	5 689	57 220 478	2 355 222	13 925 210
2011	40 458	2 190	5 859	63 338 174	2 950 626	17 245 804
2012	38 575	2 113	5 787	64 391 906	3 348 840	19 573 316
2013	36 879	2 181	5 674	73 264 367	4 420 780	24 860 262
2014	36 116	2 191	5 575	81 528 661	5 302 729	30 568 410
2015	35 316	2 105	5 593	81 172 705	5 525 803	34 341 042
2016	33 937	2 058	5 512	76 287 511	5 429 353	36 373 551

Hybrid funds have almost quadrupled between 2003 and 2016. They are passive in the sense that they attempt to weakly follow a given benchmark index but active as they have freedom to manage positions, moving away from the benchmark while maintaining a low tracking error. In an EIF, to do so, different strategies are employed: enhanced cash by using futures and other

derivatives; buying fixed income instruments; allowing for short-selling and leverage; filtering some stocks or rebalancing towards lower cap stocks; or even tax-enhancement. An IBF is a very similar instrument that has further freedom to invest outside of the main index it follows. Otherwise, they are equal as they will become active when an opportunity arises.

Although hybrid funds seem very good and are perceived by Deloitte and PwC as the future of investing (Deloitte, 2016; PwC, 2017), many academics did not find evidence of them performing significantly above their benchmarks. In fact, after fees, some show these hybrid funds underperform the index they are based on (Riepe & Werner, 1998; Weng & Wang, 2017). This result is intriguing given that investors are increasingly channeling capital inflows towards these financial products. It then seems that a more detailed and updated study is needed, one that uses a larger set of data and that studies the biggest and most efficient market: the US.

This thesis is set to analyze the performance of hybrid funds while comparing them to active and passive investments. It is important to figure out if these hybrid funds are indeed semi-passive funds that become active when they see a good opportunity that adds value, or if this is just pure marketing that increases inflows to the fund. If these funds add value, understanding if it comes from positive market timing or stock picking skills can be crucial for investors to select which funds are likely to enhance returns over the benchmark and better to include on their portfolios. Hence, the purpose of this paper is to discover if hybrid funds provide the right mix between active and passive funds, outperforming other types of funds or if they are purely a marketing move aimed at increasing inflows and fees for the management of the fund.

This study would contribute to the scarce literature on these specific hybrid funds, which are an increasingly used financial instrument, on their performance, in order to solve the puzzle of their growth. Contrary to previous studies, this thesis will use the largest dataset to date, focused on the US market. This study would also provide further insights on the main characteristics and drivers of EIF and IBF performance, ability to time the market and to pick

stocks, to help investors understand *a priori* which funds are likely to perform better. Finally, it would shed light on the relationship between these funds and the market and the relationship of investors with these funds by studying turnover-performance and flow data.

This study finds that hybrid funds indeed outperform passive and active products and are good market timers. The outperformance over active funds is due to lower fees. There is evidence that replacing traditional products by hybrid funds will improve the returns of a portfolio. Furthermore, they are truly hybrid in the sense that they do not deviate significantly from the benchmark. It also discovers that these funds find and profit from short-term opportunities that have returns materialized on the same month but the funds that trade more are not necessarily the best performing. Finally, there is no conclusive proof that investors invest more on a fund after it markets itself as a hybrid fund, without changes on the fundamentals of the fund.

The remainder of this paper is organized as follows. Section 2 summarizes relevant points in the literature and guides the hypotheses development. Section 3 describes the dataset, basic summary statistics and the methodology employed to get to the final dataset. The next section lays down the empirical design. Section 5 describes the results and the final section concludes with suggestions for further improvement.

2. Literature Review and Hypotheses Development

The first doubts on how well do active funds perform were raised by Jensen (1968). The author found that, on average, funds underperformed the market with an alpha of -0.011 net of fees, the measure he applied to financial performance. Other more recent studies propose different alpha measures that continue to be used until today (Carhart, 1997; Fama & French, 1993). While some studies advocate that active management adds value for investors, many believe this is not true after fees. Fama and French (2010) go a step further in stating that skill does not exist as the best funds are no better than efficiently managed passive funds.

Active funds have higher expenses which, *ceteris paribus*, lower the fund's net return for investors. However, funds with higher expenses may have better gross performance, and net performance as well, as these can signal the presence of good managerial skill (Ferreira, Keswani, Miguel, & Ramos, 2013). Furthermore, high transaction costs also harm the fund's performance, although they may be caused by larger turnover deriving from the search of better opportunities.

While the active fund industry is widely studied, passive funds only started receiving more attention recently. Their popularity across investors is growing as cheaper funds that are able to properly diversify portfolios. Passive investments have lower costs and their returns should not be overlooked. Malkiel (1995, 2013) is one of the most critical voices against active funds and in favor of passive management. He shows that active funds have expenses that are excessively high and did not find a significant positive relationship between expenses and gross returns, as other studies did. Carhart (1997) also shows that mutual funds are not able to consistently outperform the benchmark and Berk and Green (2004) developed a model based on decreasing returns to scale such that, as a fund becomes larger, return is likely to worsen so it explains the lack of persistence in returns. Even Warren Buffett, the most successful active investor, has advised his wife to buy passive products, according to the Berkshire Hathaway Annual Report (2013).

Nevertheless, passive funds also have some deficiencies that could be solved. For instance, pure index funds suffer from dramatically increased transaction costs during index changes. Keim and Madhavan (1997) showed that index managers had execution costs 0.45% higher than value traders. This makes sense since value traders invest actively according to the long term fundamental value of a stock so they do not need immediate completion of their orders, allowing them to use more limit orders – ensures price but not completion/quickness of the order - than indexers.

Hybrid funds, which address the abovementioned concerns, have rarely been studied. This also seems a puzzle given that a hybrid fund is found to be more efficient than a combination of pure active and passive funds (DiBartolomeo, 2000). Furthermore, the few papers on the performance of hybrid funds have either a small sample or are directed towards a specific small market. The first study on the performance of hybrid funds showed no signs of a positive alpha for eight S&P500 enhanced index funds (Riepe & Werner, 1998). Weng and Wang (2017) studied twenty nine Chinese enhanced index funds and found evidence that EIFs perform worse than their benchmarks after fees.

In terms of manager characteristics, Weng and Wang (2017) find that managers with education or work experience outside of China perform better in hybrid funds, while previous experience in other areas harms the performance of the fund. Contrary to human capital theory, higher fees do not translate into better returns.

In order for these funds to be truly considered hybrid, they must be able to closely follow a benchmark, otherwise an investor would prefer an active fund. This would mean that measures of deviation from a benchmark, such as the active share and tracking error, of hybrid funds should be lower than those of active funds but higher than pure index funds.

Hypothesis I – Hybrid funds maintain a low tracking error and low active share when compared to active funds

Using a small sample of 5 pure index funds and 3 enhanced index funds, Frino, Gallagher and Oetomo (2005) analyze the funds' trades and strategy. As expected, EIFs begin rebalancing earlier than other funds, leading to higher tracking error, and for index inclusions, they finish trading after other indexed funds. Additionally, EIFs do smaller trading orders and wait longer before completion, primarily to decrease transaction costs but also to enjoy temporary positive returns associated with the index adjustments that pure index funds are unable to get.

These studies are not performed in the biggest market, the US, and have small sets of data. Despite previous literature, since investors are still pursuing these hybrid funds, either by replacing active or passive portions of their portfolio, it is reasonable to hypothesize that they outperform the benchmark and active money management. This would imply that previous literature is wrong due to the small and specific datasets used.

Hypothesis II – Hybrid funds outperform their benchmark and similar active funds

Investing in EIFs, instead of a portfolio with a combination of active and passive funds, will “reduce transaction costs, avoid capitalization biases, and provide better utilization of manager forecasting skill” (DiBartolomeo, 2000). However, EIF managers seem to be poor stock pickers and average market timers, a result consistent for all risk-adjusted measures. Taking extreme periods where the market has returns above 10% or below -10% into consideration, there are no conclusive results. When the return is between 10% and -10%, the poor stock picking skills are confirmed and managers seem to time the market well (Weng & Wang, 2017). It would make sense that the greatest value added from these hybrid funds comes from general knowledge of market conditions, that allow them to hedge, especially when their benchmark is more exposed to downturns.

Hypothesis III – Hybrid funds are average stock pickers

Hypothesis IV – Hybrid funds are good market timers

Hybrid funds hold a larger portion of futures and instruments other than equity on their portfolios (Frino et al., 2005). They overweight stocks that have higher liquidity, higher market capitalization, better past performance and underweight low book-to-market. Some hybrid funds, the index based funds, hold positions outside of the benchmark. Frino, Gallagher and Oetomo (2005) found these to provide significant positive returns (0.13% daily), an impressive figure taking into account that the portion of their holdings different from the index is minimal.

Existing literature also relates deviation from a benchmark with performance. Using an “active share” measure, which compares the holdings of a fund with the holdings of its benchmark, Cremers and Petajisto (2009) show that funds that deviate more from the benchmark - that have a higher active share - perform better than other funds. On a different level, a similar cross-sectional relation is not corroborated by Pástor, Stambaugh and Taylor (2017) that find a positive, but not significant, relationship between fund turnover and gross returns. However, these authors are able to find a statistically and economically significant relationship between these two variables in a time series. This supports the idea that when a fund starts trading more, it is doing so to take advantage of perceived opportunities that will lead to improved future returns.

Hypothesis V – Hybrid funds trade more when they perceive an opportunity

Berk and Green (2004) created a model that seems to explain well why do some funds receive more capital inflows. Talent is rewarded with inflows but as the fund becomes larger, decreasing returns to scale happen due to liquidity constraints, higher transaction costs and because the market will monitor more closely its trades.

Cronqvist (2006) shows that marketing and advertising increase the flows entering a fund without signaling manager ability. Academics find that loads and 12b-1 fees, both proxies for marketing quality, are statistically significant and positive predictors of flows (Barber, Odean, & Zheng, 2005; Elton, Gruber, & Busse, 2004; Sirri & Tufano, 1998). All in all, initiatives that market the fund as a source of higher returns, such as labelling itself an “enhanced index” or a “hybrid” fund should increase capital inflows.

Hypothesis VI – Inflows increase after a fund names itself a hybrid fund

3. Data, Methodology and Summary Statistics

The Center for Research in Security Prices (CRSP) Survivorship-Bias-Free Mutual Fund database, accessed through the Wharton Research Data Services, is the main used source of

data. It keeps track of open-ended funds in the US, still in existence and closed, which solves the well-documented problem of survivorship bias which happens when only the funds that never disappeared are considered, inflating the average return of the market because the surviving funds are almost always the best performing among its competitors. However, it is worth noting that two biases still remain and should be addressed: (1) some historic returns may be duplicated since some funds are split (2) selection and incubation bias on some funds that started as private funds – these can report their historical returns before becoming public, while the ones who closed cannot.

The CRSP Mutual Fund database reports observations at the share-class level. Since 2003 that CRSP identifies if a fund is an index fund, hence that is the starting point for our analysis. Monthly panel data for each share-class from 2003 until 2016 was gathered, a recent dataset which eliminates the concern from the first abovementioned bias. From the CRSP tools there are monthly returns - after fees, commissions and expenses but before loads -, excess market return over the risk-free rate, risk-free rate, small-minus-big (SMB) factor, high-minus-low (HML) factor, up-minus-down (UMD) factor, risk-free rate, total net assets (TNA), date of first offer and management fund identification code. Also from CRSP, fund summary data was gathered on the fund name, index fund flag, turnover ratio, Lipper tax code, and Lipper objective code as well as fee data on 12b-1 fees, rear loads, front loads, management fees and expense ratio. Data on active share comes from the database developed on previous literature by Martijn Cremers (Cremers, Ferreira, Matos, & Starks, 2016; Cremers & Petajisto, 2009). This lead to 4 442 178 panel observations that will be treated on Stata and MatLab.

The CRSP database has some reporting issues that must be addressed. Observations without returns were dropped. Values of 0.999 or -99 on 12b-1 fees or loads mean that the fund cannot have these and were replaced by a fee equal to 0. Fund summary data has quarterly frequency, so data had to be carried forward, for each share-class, of a given quarter for the next two

months of the same quarter. Active share data was only available on a yearly basis so the same was done, assuming the active share remained constant for all months of that given year.

Some funds, such as currency, mortgage-backed, balanced, fixed income and foreign equity funds as classified in the Lipper code, were excluded for not being relevant for the analysis on hybrid funds¹. All funds with less than 38 observations were dropped so that, at least, there are 36 observations for each fund's rolling windows alpha estimation after dropping a maximum of two observations without quarterly data². Additionally, funds with TNA lower than 15M\$ were dropped to solve possible reporting errors or different conventions, even though this bias is smaller now that NASDAQ also discloses returns for these smaller funds (Amihud & Goyenko, 2013; Elton, Blake, & Gruber, 1996). These two measures also allow to partially address Evans (2010) incubation bias concerns, also stated previously. To tackle it more effectively, observations that happen before the fund's origin year are dropped, according to the author's advice, an approach also followed by Amihud & Goyenko (2013) and Cremers & Petajisto (2009)³.

Finally, CRSP reports observations at the share-class level: it splits between shares with different characteristics, despite having the same underlying fund. The object of study of this paper is at the fund level, so share-classes were collapsed month by month into funds using MFLINKS, which associates the CRSP identifier number to a given fund and was first developed by Wermers (2000). If a fund has multiple share classes, these will be aggregated in the following way: logarithm of TNA and flows using the sum of all classes; age, loads and 12b-1 fees will be the maximum value among them; factors, expense and turnover ratios,

¹ These will be included later as an extension to the primary analysis.

² If data on a fund starts on January, for instance, since the characteristics are reported quarterly starting on March, there is no data for the first two months so these observations will be dropped.

³ Another suggested solution is to drop all funds that do not have a reported fund name on CRSP. It will not be done since it would decrease to half the total number of observations and would cause collinearity. Furthermore, one could also exclude the first 36 observations of all funds, but that would also decrease dramatically the size of the sample, removing all observations between the beginning of 2003 and the end of 2005.

management fee, returns are aggregated using a weighted average using TNA as weights. All remaining variables are equal across share-classes so the first observation is used.

Numerical variables are winsorized at the 1st and 99th percentiles to exclude possible outliers and to deal with data measurement errors that may still subsist. In the end, the dataset is left with 632 632 monthly fund-level observations ranging from March 2003 until the end of 2016.

Table 2 shows basic descriptive statistics on the studied variables.

Table 2 - Summary Statistics

	(1) ACTIVE FUNDS 110893 funds				(2) ENHANCED INDEX FUNDS 1313 funds				(3) INDEX BASED FUNDS 2068 funds				(4) PURE INDEX FUNDS 6056 funds			
	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
<i>activeshare_sd</i>	0,7983	0,1385	0,1627	0,9970	0,4154	0,2511	0,0314	0,9701	0,4650	0,2563	0,0314	0,9664	0,1839	0,2553	0,0314	0,9970
<i>activeshare_min</i>	0,7553	0,1468	0,1627	0,9775	0,3955	0,2301	0,0280	0,9414	0,4477	0,2493	0,0280	0,9368	0,1585	0,2157	0,0280	0,9434
<i>actual_12b1</i>	0,0062	0,0037	0,0000	0,0100	0,0049	0,0035	0,0003	0,0100	0,0030	0,0031	0,0001	0,0100	0,0036	0,0030	0,0001	0,0100
<i>age</i>	24,465	13,908	9	75	17,826	4,2047	9	26	18,550	4,5979	10	29	19,775	6,1715	9	41
<i>exp_ratio</i>	0,0120	0,0033	0,0016	0,0230	0,0115	0,0045	0,0041	0,0223	0,0088	0,0059	0,0009	0,0230	0,0055	0,0040	0,0009	0,0230
<i>familylogtna</i>	9,4066	2,1541	3,4012	13,870	9,3321	1,0567	4,3360	11,824	9,4475	2,6258	3,4874	13,870	9,5415	1,6914	4,5737	13,870
<i>familysize</i>	25,243	31,286	1	213	27,291	14,452	2	76	29,868	28,236	2	97	25,717	19,043	1	97
<i>flows</i>	-0,1517	1,1240	-4,6891	2,1164	-0,1624	0,8196	-4,6891	1,8929	0,0142	0,9140	-4,6891	2,1164	-0,0466	0,9319	-4,6891	2,1164
<i>front_load</i>	0,0004	0,0037	0	0,0575	0	0	0	0	0	0	0	0	0,0000	0,0007	0	0,0100
<i>rear_load</i>	0,0000	0,0008	0	0,0200	0	0	0	0	0	0	0	0	0	0	0	0
<i>logtna</i>	6,4167	1,5895	2,8094	10,108	5,1602	0,9743	2,8094	6,9112	6,0677	1,7769	2,8094	8,9100	6,4651	1,4752	2,8094	10,108
<i>mgmt_fee</i>	0,7296	0,2400	-16,182	1,6437	0,5994	0,2423	-1,7940	1,3150	0,4880	0,3478	0,0550	1,9030	0,2390	0,2232	-0,3730	1,2160
<i>te</i>	0,0148	0,0067	0,0022	0,0562	0,0107	0,0099	0,0032	0,0572	0,0117	0,0070	0,0015	0,0314	0,0087	0,0076	0,0010	0,0572
<i>turn_ratio</i>	0,7266	0,6081	0,0200	5,5700	1,4443	1,2475	0,1100	5,5700	0,9909	1,2675	0,0200	5,5700	0,5111	1,2098	0,0200	5,5700
<i>mret</i>	0,0075	0,0450	-0,1281	0,1215	0,0083	0,0490	-0,1281	0,1215	0,0091	0,0455	-0,1281	0,1215	0,0082	0,0436	-0,1281	0,1215
<i>OAR</i>	0,0020	0,0143	-0,0478	0,0525	0,0004	0,0145	-0,0478	0,0525	-0,0014	0,0136	-0,0478	0,0525	-0,0005	0,0081	-0,0478	0,0525
<i>alphacapm</i>	-0,0006	0,0031	-0,0112	0,0117	-0,0012	0,0029	-0,0112	0,0117	-0,0007	0,0022	-0,0083	0,0057	-0,0003	0,0019	-0,0095	0,0115
<i>alphach</i>	-0,0007	0,0026	-0,0118	0,0102	-0,0016	0,0022	-0,0102	0,0102	-0,0009	0,0018	-0,0103	0,0046	-0,0004	0,0012	-0,0073	0,0077
<i>alphaff</i>	-0,0006	0,0028	-0,0126	0,0107	-0,0015	0,0023	-0,0101	0,0107	-0,0008	0,0019	-0,0126	0,0046	-0,0003	0,0012	-0,0098	0,0068
<i>grossalphacapm</i>	0,0117	0,0045	-0,0009	0,0246	0,0102	0,0039	0,0020	0,0246	0,0083	0,0056	-0,0009	0,0235	0,0052	0,0044	-0,0009	0,0246
<i>grossalphaff</i>	0,0117	0,0043	-0,0007	0,0240	0,0099	0,0037	0,0022	0,0240	0,0082	0,0053	-0,0006	0,0234	0,0052	0,0040	-0,0005	0,0221
<i>grossalphach</i>	0,0117	0,0042	-0,0005	0,0236	0,0098	0,0037	0,0024	0,0236	0,0082	0,0053	-0,0005	0,0235	0,0051	0,0040	-0,0005	0,0230

4. Empirical Design

4.1 Hybrid Funds and their mandate

First, it is important to determine if hybrid funds stay true to their mandate: to be allowed to deviate from a benchmark to succeed on finding profit opportunities (Green & Jame, 2011).

However, if they do in such a way that is similar to active funds, the name “hybrid” no longer

makes sense. It would be a marketing move to take advantage of a market niche because, in reality, they would simply be active funds.

Deviation from a benchmark is traditionally measured using the tracking error, which is the standard deviation of the residuals of the capital asset pricing model (CAPM), shown in Equation 1, a regression of excess returns on the excess return of the market as explained in Cremers & Petajisto (2009) and Zambrana & Zapatero (2015). These authors argue that the tracking error is not a good measure of deviation from a benchmark.

$$r_{i,t} - r_{f,t} = \alpha_{CAPM,it} + \beta_{MRP,it} \cdot (r_{m,t} - r_{f,t}) \quad (1)$$

Tracking error is related to diversification, not just to the share of the portfolio that is equal to the benchmark. This means that the tracking error does not show fund activity, as a fund that invests in many components of different indices will have a low tracking error, because it is well diversified, although it invests in many assets outside of the benchmark. To solve this, Cremers & Petajisto (2009) created the active share measure, which is the “fraction of the portfolio that is different from the benchmark index”. It solves the abovementioned problem of tracking error, so although both measures to define active management will be used, the active share measure is more likely to provide an accurate result. Amihud and Goyenko (2013) use the R^2 of a benchmark regression to proxy for active management but it does not add significant differences from tracking error and active share.

To study differences in active management among active, passive and hybrid funds, a simple t-test to the difference of means of active share and tracking error, winsorized at the 1st and 99th percentiles, will be performed.

4.2 Hybrid Funds versus Passive Investments

To study the second hypotheses, if hybrid funds outperform the benchmark, an alpha for each fund will be computed using the models of Jensen (1968), Fama and French (1993) and Carhart (1997), shown in Equations 1-3 respectively. A positive alpha is a sign of outperformance over

a benchmark. Showing, through a t-test, if the alphas of hybrid funds are positive and statistically significant will confirm this hypothesis.

$$r_{i,t} - r_{f,t} = \alpha_{FF,it} + \beta_{MRP,it} \cdot (r_{m,t} - r_{f,t}) + \beta_{SMB,it} \cdot SMB_t + \beta_{HML,it} \cdot HML_t \quad (2)$$

$$r_{i,t} - r_{f,t} = \alpha_{CH,it} + \beta_{MRP,it} \cdot (r_{m,t} - r_{f,t}) + \beta_{SMB,it} \cdot SMB_t + \beta_{HML,it} \cdot HML_t + \beta_{UMD,it} \cdot UMD_t \quad (3)$$

,where $r_{m,t} - r_{f,t}$ is the excess return of the market over the risk-free rate (market risk premium – MRP); SMB is a portfolio of stocks that goes long on firms with small market capitalization and short on stocks with big market capitalization; HML is a portfolio of stocks that goes long on firms with high book-to-market ratios and short on firms with low book-to-market ratios and UMD is a portfolio of stocks that goes long on stocks that have been having a positive return trend and short on stocks that have been having a negative return trend, relating it to a momentum strategy.

4.3 Hybrid Funds versus Active Investments

To check if hybrid funds are better than otherwise similar active products, a time series of rolling windows alphas has to be estimated. These alphas are the relevant performance measures after fees so they will be the dependent variable on the regression that tests the effect on performance of being a hybrid fund, when including hybrid and active funds. The alphas will be net of fees, that uses monthly return net of expenses, and also the gross alpha, that utilizes the return before expenses⁴, using Equations 1-3.

The independent variables are a dummy that takes the value of 1 if the fund is a hybrid fund and 0 if it is an active fund, plus some controls. Put simply, this dummy variable will show if the alphas of hybrid funds are higher than the alphas of active funds. From the descriptive statistics of Table 2, it seems that characteristics are correlated with the type of fund. For

⁴ As an extension, for all types of funds, the objective adjusted return (OAR) will also be computed. It is equal to the difference between the monthly net return and the median of monthly net returns of funds with the same style, as reported by the Lipper code. This is similar to the measure used in Khorana & Servaes (1999) and Evans (2010) which adjust returns to the style of the fund.

instance, it seems that hybrid funds are the youngest, the smallest, have lower front and rear loads and have the highest turnover. Active funds are the most expensive, have larger outflows, larger loads, are inside the smallest management families - a family is the management company that sells different funds - in number of funds and TNA, largest tracking error and active share. Passive funds have larger inflows, lower tracking error and active share, while the hybrid funds fall in-between the other two groups. Therefore, the controls in the regressions will be size, measured as the log of TNA, age, flows, family size, family TNA, turnover ratio, expense ratio, active share from the self-reported benchmark, front load and rear load. Pure index funds will be excluded from the sample since the comparison is now between active and hybrid products.

For this, different models test different implications. The first regression is a pooled ordinary least squares (POLS) without controls. The second specification adds the controls. The third model is a POLS of time fixed effects for panel data, so that it isolates performance from months in which the general market trend was positive or negative, with standard errors clustered by fund. The fourth model is POLS with family and time fixed effects, to control for months with abnormal performance and for unobservable family characteristics, such as the power of the machines they use, the quality of the trading desk and managers, synergies with other funds of the same family, economies of scale, among others. With the family fixed effects, one can compare the performance of a hybrid fund against the performance of a non-hybrid product from the same fund family. On this specification, the family controls used previously are dropped because they are all being accounted for on the family fixed effects. In specifications three and four, the standard errors are clustered by fund. This prevents a typical form of heteroscedasticity present in panel data because, in the dataset used, there are unobservable fund characteristics that, with OLS standard errors, create a predictable pattern in the errors of the regressions that depends on the cluster which is the fund (Petersen, 2009).

The fifth model is a Fama-MacBeth (FMB) model (Fama & MacBeth, 1973) with Newey-West robust standard errors that correct for serial correlation (Newey & West, 1987). The FMB model has two stages: on the first stage, a regression is performed for each month in the sample; on the second stage, the final coefficients estimated are the averages of all the coefficients in the first step. Since monthly specific unobservable factors are being left in the residuals of each monthly regression, this means that we are isolating the cross-sectional determinants of performance to discover which type of funds are likely to perform better.

One could argue that this approach is not accurate if the idiosyncratic risk of active and EIF funds is different given that they may hold positions in very different assets. This is specific risk that each asset is exposed to and is captured on the residuals of the factor regressions, such as the CAPM or FF. Hence, a Sharpe Ratio (SR) for each fund will be computed using the available observations. The SR is equal to the excess fund return over the risk-free rate, divided by the fund return volatility. It shows the risk-adjusted return of a financial product: it no longer conditions the performance measure to the factors used so it controls for different idiosyncratic risk. Then, a t-test between the SR mean of active and hybrid funds will be calculated.

4.4 Stock Picking and Market Timing Skills

After discovering if hybrid funds outperform other products or not, it is important to disentangle between the results from stock picking and market timing. Stock picking is the ability to select stocks that, on average, outperform while market timing shows the ability to increase exposure to the benchmark portfolio when the market conditions are good and to increase exposure to safer assets, or the risk-free asset, when the market is not favorable. To study this, both the Treynor & Mazuy (1966) and the Henriksson & Merton (1981) models will be used. These are the most commonly used methods in Finance to discover the abovementioned abilities (Daniel & Moskowitz, 2016; Weng & Wang, 2017; Zambrana & Zapatero, 2015).

The Treynor-Mazuy (TM) includes a squared market term to the FF equation while the Henriksson-Merton (HM) interacts a market condition dummy with the market risk premium. On this thesis, a dummy equal to 1 when the MRP is positive and 0 otherwise will be used. Both are designed to split the FF alpha between a market timing component – the new term which, if positive, shows increased exposure to the market when the market has better returns – and a stock selection component which is the remainder of the FF alpha, captured in this model's own alpha. TM models this in convexity because as MRP increases, the return increases more than proportionately due to the squared term while the HM seems like a call option outcome that only has value for higher MRP levels.

On the HM model, one must be careful because it can display heteroscedasticity. One solution is using General Least Squares or using the White and Hansen heteroskedastic-robust standard errors. Breen, Jagannathan & Offer (1986) found that the latter provides the best correction for heteroscedasticity so it will be used.

4.5 Turnover-Performance Relationship

To test whether hybrid funds become active, i.e. trade more, when they see an opportunity, it is important to show the relationship between the turnover ratio and performance. The turnover ratio is a measure of activity of a fund since it is the minimum of aggregated sales or purchases of securities divided by the average 12-month TNA, as defined by CRSP.

This section only want to discover if hybrid funds are able to identify and capitalize on opportunities, not if they deliver superior returns after fees or if they outperform a benchmark. For this reason, the independent variable is gross returns, not net returns or alphas, following Pástor, Stambaugh and Taylor (2017). The relevant dependent variable is the lagged turnover. A positive coefficient on the lag of turnover indicates that the funds are finding opportunities that lead to higher returns in the next month. One limitation of this is the fact that the only considered opportunities are discovered in the previous month to the month in which the returns

are materialized. Although this should capture the majority of a hybrid fund's decisions, it could be leaving out opportunities that have their return materialized on the same month or that take longer than one month.

The same authors dissect this turnover-performance relationship between time-series and cross-sectional dimensions. The first tries to discover if, when one hybrid fund starts trading more, it is doing so to capture profit opportunities while the latter may indicate if hybrid funds that trade more achieve better performance or if a high turnover is just a strategy to show activity to investors. It is well known that the incentives of active, and also hybrid funds, are to trade often, otherwise investors will feel that it is best to have their savings parked in a passive low-cost fund.

Instead of mimicking the POLS model of Pástor, Stambaugh and Taylor (2017) a FMB model with Newey-West standard errors is used, as well as a POLS with family and time fixed effects to check the cross-sectional relation as previously. For the time-series it is a POLS with fund fixed effects and clustered standard errors with and without time dummies. The fund fixed effects allow for the relationship to be studied for each fund over time.

4.6 Fund Flows

To test the final hypothesis, fund flows will be measured as in Sirri and Tufano (1998) and Cooper, Gulen and Rau (2005): $\text{Fund Flows} = [\text{TNA}_t - (1 + r_t)\text{TNA}_{t-1}]/\text{TNA}_t$, where TNA is total net assets and r is the return over the previous month. One simple way to test it is to create a signal when a fund changes its classification from active to hybrid. Given the small number of signals, this does not yield consistent estimates.

To test this hypothesis more accurately, the propensity score matching approach of Cooper, Gulen and Rau (2005) is followed. The propensity score consists on estimating a logistic regression where the dependent variable is a dummy of 1 when the fund names itself a hybrid fund and 0 otherwise. The regressors will be the variables the literature has proven to have an

impact on flows. Following Cooper, Gulen and Rau (2005), the controls will be size, age, lagged flows, 12b-1 fees and the Fama-French alpha. Then, each fund that has changed category will be matched with a fund that has not and that has the closest propensity score for the characteristics, until a maximum possible difference of 0.1%. The final step is to compute the difference in flows between two groups, one with name changes and the other one without. All the analysis will be done on Stata.

5. Results and Discussion

5.1 Hybrid Funds and their mandate

Hybrid funds have lower active share, higher tracking error and higher turnover ratio than active funds. These differences are significant at the 0.1% level as shown in Table 3. Hence, it appears that hybrid funds stay true to their mandate because they do not deviate significantly from the benchmark, whether we consider the active share with respect to the reported benchmark or the benchmark with the smallest active share. Tracking error has the opposite interpretation but it may be due to the limitations of this measure, discussed previously. In fact, hybrid funds may have higher tracking error than active funds because they are not as diversified, they have to stay close to the industries and components of a specific index.

Table 3 - T-test of Means between Active and Hybrid Funds

<i>te</i>	-0.000297***	(-3.47)
<i>activeshare_sd</i>	0.316***	(176.06)
<i>activeshare_min</i>	0.258***	(164.98)
<i>turn_ratio</i>	-0.477***	(-68.72)
<i>N</i>	520434	
t statistics in parentheses		
* p<0.05	** p<0.01	*** p<0.001

The result on turnover is more surprising as one would expect hybrid funds to trade very little, just enough to capture opportunities they see. One possible explanation is that because they are the funds with the lowest TNA, any purchase or sale of securities will have a large impact on turnover. Furthermore, if they take large positions on a small set of index components and they have to change these bets completely often, then the turnover will become large.

5.2 Hybrid Funds versus Passive Investments

Following with the performance puzzle: doing a t-test on the null hypothesis of hybrid fund's Carhart model alpha lower or equal than 0 against the alternative that alpha is positive has a p-value of 8.88% with an average alpha of 0.04927%. This means that, at a 10% significance level, hybrid funds outperform the benchmark, even after fees. Finally, there appears to be some evidence that supports the decision from investors to increase their exposure to these hybrid funds. This result is also robust to the other two models used.

5.3 Hybrid Funds versus Active Investments

Relative to net performance against active funds, seen in Table 4-Panel A, the alpha of hybrid funds without controls nor fixed effects is lower than the alpha of active funds as shown in the summary statistics. In POLS without fixed effects but adding controls, it seems that hybrid funds deliver superior performance after fees, due to a positive coefficient on the hybrid dummy. Hence, hybrid funds seemed worse than active funds because their characteristics are not favorable: namely, they are smaller while size affects performance positively. If characteristics, which are correlated with performance, are included in the picture, then, *ceteris paribus*, these hybrid products outperform.

Table 4 - Hybrid Funds' Performance

Panel A: Net Alphas															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	CAPM	FF	Carhart	CAPM	FF	Carhart	CAPM	FF	Carhart	CAPM	FF	Carhart	CAPM	FF	Carhart
hybrid	-0.00084*** (-25.61)	-0.00077*** (-24.45)	-0.00068*** (-22.25)	0.00033*** (7.98)	0.00042*** (11.48)	0.00026*** (7.56)	0.00064*** (2.99)	0.00056*** (3.03)	0.00037** (2.11)	0.00085*** (3.94)	0.00080*** (3.95)	0.00065*** (3.20)	0.00055*** (3.08)	0.00043*** (4.29)	0.00024** (2.14)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Month F. E.	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	FMB Model	FMB Model	FMB Model
Family F. E.	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	FMB Model	FMB Model	FMB Model
N	453864	453864	453864	185360	185360	185360	185360	185360	185360	185360	185360	185360	185360	185360	185360
Panel B: Gross Alphas															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	CAPM	FF	Carhart	CAPM	FF	Carhart	CAPM	FF	Carhart	CAPM	FF	Carhart	CAPM	FF	Carhart
hybrid	-0.00200*** (-42.62)	-0.00216*** (-47.83)	-0.00220*** (-49.87)	0.00007* (1.67)	0.00018*** (4.62)	0.00003 (0.82)	0.00033* (1.66)	0.00028 (1.61)	0.00010 (0.60)	0.00054** (2.56)	0.00049** (2.38)	0.00034 (1.61)	0.00027 (1.34)	0.00016 (1.58)	-0.00002 (-0.14)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Month F. E.	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	FMB Model	FMB Model	FMB Model
Family F. E.	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	FMB Model	FMB Model	FMB Model
N	248363	248363	248363	180679	180679	180679	180679	180679	180679	180679	180679	180679	180679	180679	180679
t statistics in parentheses															
* p<0.1 ** p<0.05 *** p<0.01															

After adding month fixed effects and/or family fixed effects, the results are confirmed. Even with the FMB model, there is a statistically significant difference between the alphas of active

and hybrid funds: the latter type outperforms the first⁵. The previous results may be driven by the higher fees charged by active funds. An analysis to gross alphas in Table 4-Panel B confirms it. Although there is mild evidence of higher alphas in POLS with time fixed effects and with or without family fixed-effects, this disappears in the FMB model. Therefore, hybrid funds are creating more value than active funds, due to the lower fees they charge. Thus, the results achieved by previous literature are not being confirmed on this larger and more efficient US market: on aggregate, hybrid funds are better than a passive investment on a benchmark proxy and, after fees, they are also better than active funds.

By regressing the alphas on fund characteristic, one can see that hybrid funds that are older, in larger families and that trade more seem to perform better. In fact, if the analysis is repeated but only considering the quartile with the largest families in number of funds, then the economic significance of the results increases⁶, showing synergies between funds.

The SR of hybrid funds is also higher, on average, than the SR of active funds. This means that hybrid funds have higher risk-adjusted returns. The average difference between these fund types is 0.0473 and is statistically significant at the 0.01% significance level which confirms the previous results.

5.4 Stock Picking and Market Timing Skills

These performance measures can be split into market timing and stock selection skills using the TM and HM with White standard errors models. Both models yield consistent and statistically significant results: although hybrid funds are good market timers, since the market coefficient is positive, they are not able to select well the stocks in their portfolio. The models have opposite signs for the constant that signals stock selection but none is significant. As

⁵ The same analysis was done using the OAR, but including all types of funds and style dummies. A positive alpha is discovered but it is only significant at the 10% level in POLS with fixed effect and not significant in the FMB. This result may be due to the very specific investment objectives: it is unlikely that, inside each style, some funds dramatically outperform others. Results, split by sector, are shown in the appendix.

⁶ The coefficients on the hybrid dummies increase. Results shown in the appendix.

argued previously, a pure index fund cannot hedge against seasons where the index they track is likely to behave poorly. Hybrid funds, however, are able to decrease their exposure to the index. At least, they can reduce their positions on the securities most affected by the downturn. The lack of stock selection ability may follow from human capital theory. Maybe the managers hired to run hybrid funds are not good stock pickers themselves so this will not be the fund's comparative advantage.

Table 5 - Treynor-Mazuy and Henriksson-Merton Models on Hybrid Funds

	(1) TM	(2) HM
<i>mktrf</i> ²	0.77900*** (11.74)	
<i>mktrf</i> * <i>MD</i>		0.12829*** (8.55)
<i>constant</i>	0.00022 (0.46)	-0.00039 (-0.82)
<i>N</i>	19038	19038
t statistics in parentheses		
* p<0.1, ** p<0.05, *** p<0.01		

5.5 Turnover-Performance Relationship

Next, let us try to discover if a hybrid fund is finding and capitalizing on opportunities discovered. From a cross-sectional perspective, using the FMB model or family and month fixed effects, models 1 and 2 of Table 6 respectively, there is no evidence of an increase in gross returns after a turnover increase.

Interestingly, in a time series approach with fund fixed effects and without a dummy for each month, turnover positively affects gross return but the lag of turnover negatively affects it. This provides support to the fact that the opportunities that arise to hybrid funds have a short-term character since they are discovered and have returns on the same period. On a longer time span, the opportunity effect vanishes and as the opportunity, perhaps some inefficiency on a stock price, disappears or reverts, we observe a negative turnover-performance relationship. This is consistent with the idea that hybrid funds add more value around index change periods given that they provide return opportunities on the very short term.

Table 6 - Turnover-Performance Relationship

	(1)	(2)	(3)	(4)
<i>Turnover</i>	-0.17382 (-0.47)	-0.00079 (-0.67)	0.00599** (2.12)	0.00173 (1.10)
<i>Lag of Turnover</i>	0.17348 (0.47)	-0.00026 (-0.22)	-0.00487* (-1.76)	-0.00196 (-1.26)
<i>N</i>	14177	14177	14177	14177
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Family F.E.</i>	FMB Model	Yes	No	No
<i>Month F.E.</i>	FMB Model	Yes	No	Yes
<i>Fund F.E.</i>	FMB Model	No	Yes	Yes
t statistics in parentheses				
* p<0.1, ** p<0.05, *** p<0.01				

5.6 Fund Flows

After a fund names itself a hybrid fund, there is an increase in inflows on that month and on the following couple of months but this POLS with signal is not significant for 152 cases. This result is significant using a logit on the one-to-one propensity score matching. A newly instituted hybrid fund does experience added inflows with respect to an otherwise similar fund. Perhaps, investors are aware that hybrid funds are likely to perform better so they invest more on a newly named hybrid fund just because of the type change.

The results are shown in Table 7, robust to different procedures except for the radius matching when a fund is matched with all funds inside of the 0.1% score difference. Since the score difference is small, these are very similar funds that should not have difference in inflows, corroborated with the Radius matching. All in all, evidence is mixed but ultimately investors are not increasing inflows to these funds just because of the change in type.

Table 7 - The impact of type change on flows

	Coefficient	T-stat
<i>POLS using Signal</i>	0.12669	0.60
<i>Propensity Score Matching using One-to-One Matching</i>	0.04750	2.64***
<i>Propensity Score Matching using Radius Matching</i>	0.01652	1.26
<i>Propensity Score Matching using Kernel Matching</i>	0.05450	4.32***
* p<0.1, ** p<0.05, *** p<0.01		

6. Conclusion

In conclusion, this thesis refuted the results that previous literature had achieved and added some insights on the determinants of hybrid fund performance, the turnover-performance relationship and on the way investors look at these funds. It is different because, on aggregate,

it found that hybrid funds outperform their benchmarks, which is likely to have happened due to the more extensive and efficient dataset used. It discovered strong evidence of hybrid funds achieving higher alphas than active funds. Looking at gross alphas, the results vanish. There was only weak evidence to support the claim that, before fees, hybrid funds generate higher alphas than active funds. Nevertheless, they generate a positive alpha, so they are better than their benchmarks and after fees they are better than active funds.

This thesis added further insights in the sense that it discovered that hybrid funds are poor stock pickers but are able to time well the market. Furthermore, it proved that hybrid funds are able to discover short-term opportunities to become active that improve their returns within the same month such as index changes. Finally, there is mixed evidence if investors channel more inflows to hybrid funds when they self-report themselves as an enhanced index or index based fund, so it is not certain if they are chasing these products or if the marketing of hybrid funds is working well.

On the one hand, it seems that some hybrid funds can outperform their benchmarks and provide the right combination of active and passive strategies although it would be very ambitious to claim these are the future of investing. On the other hand, it also appears that hybrid funds are not dramatically better and can only capitalize on short-term opportunities.

Future research should build on newer datasets with more hybrid fund observations or divide the data by different periods. It should also study more in depth the marketing of these hybrid funds, if investors are really aware of their characteristics by using fund prospectuses. Furthermore, it could exploit deeper the economic significance of the results: if the magnitude of the differences is large enough so that investors will use more hybrid funds on their portfolios. On this thesis, due to time constraints, there was no manual check if a fund reported by CRSP as a hybrid fund is really hybrid. Nevertheless, this study was able to shed light on the apparent puzzle of hybrid fund growth.

References

- Amihud, Y., & Goyenko, R. (2013). Mutual Fund's R2 as predictor of performance. *Review of Financial Studies*, 26(3), 667–694.
- Barber, B. M., Odean, T., & Zheng, L. (2005). Out of Sight, Out of Mind: The Effects of Expenses on Mutual Fund Flows. *Journal of Business*, 78(6), 2095–2119.
- Berk, J. B., & Green, R. C. (2004). Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy*, 112(6), 1269–1295.
- Breen, W., Jagannathan, R., & Ofer, A. R. (1986). Correcting for Heteroscedasticity in Tests for Market Timing. *Journal of Business*, 59(4), 585–598.
- Buffett, W. (2013). Berkshire Hathaway Annual Report 2013.
- Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52(1), 57-82.
- Cooper, M., Gulen, H., & Rau, P. (2005). Changing Names with Style: Mutual Fund Name Changes and Their Effects on Fund Flows. *The Journal of Finance*, 60(6), 2825–2858.
- Cremers, K. J. M., Ferreira, M. A., Matos, P., & Starks, L. (2016). Indexing and Active Fund Management: International Evidence. *Journal of Financial Economics*, 120(3), 539–560.
- Cremers, K. J. M., & Petajisto, A. (2009). How Active Is Your Fund Manager A New Measure That Predicts Performance. *Review of Financial Studies*, 22(9), 3329–3365.
- Cronqvist, H. (2006). *Advertising and Portfolio Choice*.
- Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, 122(2), 221–247.
- Deloitte. (2016). *2017 Investment Management Outlook*.
- DiBartolomeo, D. (2000). The Enhanced Index Fund as an Alternative to Indexed Equity Management. *Northfield Information Services, Boston*.

- Elton, E. J., Blake, C. R., & Gruber, M. J. (1996). Survivorship Bias and Mutual Fund Performance. *The Review of Financial Studies*, 9(4), 1097–1120.
- Elton, E. J., Gruber, M. J., & Busse, J. A. (2004). Are Investors Rational? Choices among Index Funds. *The Journal of Finance*, 59(1), 261–288.
- Evans, R. (2010). Mutual Fund Incubation. *The Journal of Finance*, 65(4), 1581–1611.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56.
- Fama, E. F., & French, K. R. (2010). Luck Versus Skill in The Cross-Section of Mutual Fund Returns. *The Journal of Finance*, 65(5), 1915–1947.
- Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *The Journal of Political Economy*, 81(3), 607–636.
- Ferreira, M. A., Keswani, A., Miguel, A. F., & Ramos, S. B. (2013). The Determinants of mutual fund performance: A cross-country study. *Review of Finance*, 17(2), 483–525.
- Frino, A., Gallagher, D. R., & Oetomo, T. N. (2005). The Index Tracking Strategies of Enhanced Index Equity Funds. *Australian Journal of Management*, 30(1), 23–55.
- Green, T. C., & Jame, R. (2011). Strategic trading by index funds and liquidity provision around S&P 500 index additions. *Journal of Financial Markets*, 14(4), 605–624.
- Henriksson, R. D., & Merton, R. C. (1981). On Market Timing and Investment Performance. *Journal of Business*, 54(4), 513–533.
- Jensen, M. C. (1968). The performance of mutual funds in the period 1945-1964. *The Journal of Finance*, 23(2), 389–416.
- Keim, D., & Madhavan, A. (1997). Transactions costs and investment style: An inter-exchange analysis of institutional equity trades. *Journal of Financial Economics*, 46(3), 265–292.
- Khorana, A., & Servaes, H. (1999). The Determinants of Mutual Fund Starts. *The Review of Financial Studies*, 12(5), 1043–1074.

- Malkiel, B. G. (1995). American Finance Association Returns from Investing in Equity Mutual Funds 1971 to 1991. *The Journal of Finance*, 50(2), 549–572.
- Malkiel, B. G. (2013). Asset Management Fees and the Growth of Finance. *Journal of Economic Perspectives*, 27(2), 97–108.
- Morningstar Direct Asset Flows Commentary. (2017). Morningstar Direct SM Asset Flows Commentary: United States.
- Newey, W. K., & West, K. D. (1987). A Simple Positive-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55, 703–708.
- Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2017). Do Funds Make More When They Trade More? *Journal of Finance*, 72(4), 1483–1528.
- Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, 22(1), 435–480.
- PwC. (2017). *Asset Management 2020: A Brave New World*.
- Riepe, M. W., & Werner, M. D. (1998). Are enhanced index mutual funds worthy of their name? *The Journal of Investing*, 7(2), 6–15.
- Sirri, E. R., & Tufano, P. (1998). Costly Search and Mutual Fund Flows. *The Journal of Finance*, 53(5), 1589–1622.
- Treynor, J., & Mazuy, K. (1966). Can mutual funds outguess the market. *Harvard Business Review*, 44(4), 131–136.
- Weng, Y.-C., & Wang, R. (2017). Do Enhanced Index Funds Truly Have Enhanced Performance? *Emerging Markets Finance and Trade*, 53(4), 819–834.
- Wermers, R. (2000). Mutual fund performance: An empirical decomposition into stock-picking, style, transaction costs and expenses. *The Journal of Finance*, 55(4), 1655–1695.
- Zambrana, R., & Zapatero, F. (2015). A tale of two types: Generalists vs. specialists in mutual funds asset management spillover effect tests. *Working Paper*.